Fuzzy Inference System and Neuro-Fuzzy Systems for Analog Fault Diagnosis

Mohamed El-Gamal[*1], Samah El-Tantawy[2]

[*1,2]Engineering Mathematics and Physics Department, Cairo University, Faculty of Engineering
[*1]The American University in Cairo, [*2]University of Toronto
[*1]Cairo, [2]Egypt
*mhgamal@aucegypt.edu;[2]samah.el.tantawy@utoronto.ca

Abstract

A Fuzzy Inference System (FIS) is built to model and classify faults in analog circuits. The measurements that characterize the circuit under test (CUT) behavior are selected using feature extraction and dimensionality reduction techniques. These measurements are utilized to construct a rule based system that relates measurements (symptoms) to different faults (causes). In addition, hybrid neuro-fuzzy systems are also constructed and trained to isolate the CUT faults. The integration of FIS and neural networks in these systems combines the remarkable pattern recognition capabilities of neural networks with the ability of fuzzy logic to incorporate and interpret linguistic knowledge. As a result, a superior diagnosis performance is obtained even if the CUT has overlapping faults. A benchmark circuit iS tested to demonstrate the high classification performance of the proposed procedure.

Keywords

Analog Circuits; Fault Diagnosis; Fuzzy Inference System; Neural Network; Neuro-fuzzy System

Introduction

Fault diagnosis of analog circuits is conceptually divided into two main phases; fault detection and fault isolation. In the fault detection phase, the circuit is characterized as faulty. The faulty elements or regions are identified in the fault isolation phase. By a fault, we mean any change in the value of a circuit element with respect to its nominal value that can cause the failure of the circuit performance.

Fault diagnosis of analog circuits is a challenging task due to the following reasons [Bandler & Salama (1985), El-Gamal (1990)]:

- The inaccuracy in circuit measurements besides the inability of measuring current without breaking the circuit connections.
- The tolerance in circuit elements often complicates the fault diagnosis process.
- The limited accessibility to circuit nodes especially in modern integrated circuits.
- The lack of good fault models since analog circuits have a continuum of possible faults.

Traditional methods are found inefficient in tackling the fault diagnosis problem. On the other hand, Artificial Intelligent (AI)-based techniques are found promising in overcoming the difficulties stated above [Ahmed & Cheung (1994), El-Gamal & Abu-El-Yazeed (1999)]. A comprehensive review of AI techniques used in fault diagnosis of analog systems is presented by Fenton et al. and Rutkowski and Grzecha [Fenton et al. (2001), Rutkowski & Grzecha (2008)]. Generally, AI techniques can be classified to traditional, model based, machine learning and soft computing-based techniques. Fuzzy logic system, Neural Network (NN) and hybrid neuro-fuzzy techniques are examples of soft computing-based techniques.

A fuzzy logic expert system is an expert system that uses fuzzy logic. In other words, a fuzzy expert system is a collection of fuzzy sets and rules that are used to reason about data. Fuzzy systems can be broadly categorized into two families. The first includes linguistic models based on collections of IF–THEN rules, whose antecedents (IF parts) and consequents (THEN parts) utilize fuzzy linguistic values (e.g. Mamdani FIS [Mamdani & Assilian (1975)]). The second category, based on Sugeno-type systems [Takagi & Sugeno (1985)], uses a rule structure that has fuzzy antecedent and functional consequent parts.

The analog faulty circuits are usually associated with imprecision and uncertainty. Therefore, the faulty circuit as is an excellent testbed for fuzzy systems [El-Gamal M.A., Abdulghafour (1996)]. Fuzzy logic systems behavior can be explained based on fuzzy

rules and thus their performance can be adjusted by tuning the rules. Therefore, fuzzy logic systems are good at explaining their decisions because it can reason with imprecise information. However, knowledge acquisition is not always trivial task so the applications of fuzzy systems are restricted to the small analog circuit problems where expert knowledge is available and the number of input variables is small.

On the other hand, NN is one of the state of the art approaches that has remarkable results in the fault diagnosis problem [El Gamal (2002), El Gamal & Mohamed (2007)]. However, it is neither possible to extract structural knowledge (rules) from the trained NN nor it is possible to integrate special information about the problem into the NN in order to simplify the learning procedure which makes the learning process relatively slow and the analysis of the trained network difficult (black box).

Therefore, the synergism of fuzzy systems and NN using neuro-fuzzy systems is plausible to enable the diagnosis system to deal with perception uncertainties in a manner more like humans, and to overcome the problem of knowledge acquisition. In addition, neuro-fuzzy systems will enable the NN to start with any known information about the problem in order to simplify and speed up the learning procedure by reducing the probability of entrapping in local minimum which is a major problem of NN. Moreover, neuro-fuzzy systems enable the rules in the fuzzy systems to be tuned automatically.

This paper proposes a FIS for Analog Circuits Fault Diagnosis (FIS-ACFD) using Mamdani FIS. The paper also investigates the utilization of the proposed FIS-ACFD as the basic structure for the neuro-fuzzy system to start with. The ability of neuro-fuzzy approaches to overcome the drawbacks of standalone FIS or NN is tested using two benchmark analog circuits.

The paper is organized as follows; Section 2 describes the general architecture of the fault diagnosis model. The proposed FIS-ACFD is illustrated in section 3. Different types of hybridization of fuzzy logic systems and neural networks are briefly discussed in section 4. Three state-of-the-art neuro-fuzzy systems are briefly outlined in section 5. A benchmark circuit example is examined in section 6 to demonstrate the diagnosis performance of the proposed approach and to compare the performance of different neuro-fuzzy systems. In section 7, the final conclusions are drawn.

Diagnostic System Architecture

The fault diagnosis system involves three basic modules, simulation, preprocessing, and classification. The classification module has two basic subsystems, one for training and the other for testing. First, the set of anticipated faults of the CUT is defined, simulated and the training and testing data are collected. The collected data are preprocessed in the second step. Finally, the preprocessed training data are utilized to construct the classifier while the testing data are used to test the performance of the classifier. The classifier can be either a FIS that is created using fuzzy clustering or a neuro-fuzzy system.

Simulation Phase

A selected set of possible faults of the CUT is first defined as fault classes with particular indices 1, 2,….K, where K is the number of possible faults of the CUT. Fault free situation is considered as fault class with index 0. In particular, a given fault is applied to the CUT, and the circuit simulation is performed in the presence of the introduced fault. A set of measurements is extracted from every simulation and arranged in a vector called the measurement vector which is considered as a pattern characterizing the given fault class. To obtain a number of different measurement vectors belonging to a particular fault class, the circuit with this fault is simulated more than once by changing the fault-free circuit elements around their nominal values but within their accepted tolerance. Finally, different measurement vectors belonging to a particular fault class are grouped into an $N \times M$ matrix, where N is the number of circuit simulations (Mont Carlo simulations) and M is the number of measurements.

Preprocessing phase

Applying various data preprocessing techniques to the components of the measurement vectors maps these vectors to another set of vectors called the feature vectors, or the pattern vectors, which are supposed to be more efficient in characterizing the corresponding fault classes; hence the total complexity of the system can be reduced. In addition it helps in increasing the accuracy of the system where redundant and dependent parts of the measurement are suppressed.

Feature vectors should be either of the same or of lower dimension than the measurement vectors. Parameters of data preprocessing techniques that are calculated during the training phase are also used with the testing set during the testing phase.

In this paper, Wavelet Transform (WT) [Aminian M., and Aminian (2000)] is used as a feature extraction technique. In addition, the Principle Component Analysis (PCA) [Jain (1989)], which is basically a dimensionality reduction technique, is utilized.

As a result of preprocessing phase, each fault class is presented by $N \times R$ matrix, where R is the number of reduced features, $R \leq N$. This matrix is in general partitioned to $N_t \times R$ training matrix (X) and $N_s \times R$ testing matrix(X_s), where N_t and N_s are the number of training and testing examples corresponding to each fault respectively.

Training Subsystem

Training subsystem is divided into two main phases: a building phase that sets up the basic structure of the diagnosis system, and a learning phase that modifies that structure in order to enhance the classifier's performance.

1) *Building Phase*

The basic structure of the diagnosis system represents the starting point of the learning phase; therefore, building the classifier should be accurately designed in order to reduce the probability of entrapping in local minimum.

2) *Learning Phase*

The second step in the training task is applying a learning technique that change the classifier's parameters in order to enhance the diagnosis performance of the classifier using the training data.

Testing Subsystem

In the testing phase, the feature pattern is introduced to the classifier and the same preprocessing is applied. The classifier predicts the fault class that corresponds to the applied input pattern.

The performance of the classifier is determined based on the following criteria

Recall capability: refers to the system's ability to diagnose accurately when it is tested with the training patterns.

Adaptability (Generalization): refers to the system's capability in diagnosis when it is tested with testing patterns.

The Proposed FIS for Analog Circuits Fault Diagnosis (FIS-ACFD)

Mamdani FIS consists of three main components: (1) fuzzifier, (2) rule base, and (3) defuzzifier [Jang et al. (1997)]. The customization of each component for the fault diagnosis task is described below.

Training Subsystem

The building phase includes four main tasks: the definition of inputs and their fuzzy sets, construction of the rule base, determination of fuzzy reasoning operators, and finally identification of the defuzzification process.

To perform aforementioned tasks, the training data should be constructed. The training data consists of the input training patterns in matrix X with $N_t\,.(K+1)$ rows and R columns and corresponding output target matrix Y with $N_t.(K+1)$ rows and $(K+1)$ columns; $Y=[y_{ij}]$, where

$$y_{ij} = \begin{cases} 1 & if\ the\ i^{\ th} pattern\ belongs\ to\ the\ j^{th}\ fault\ class \\ 0 & otherwise \end{cases} \quad (1)$$

where $i = 1,2,\ldots,N_t.(K+1)\ and\ j = 1,2,\ldots,K+1$.

1) *Defining the Inputs*

Inputs of FIS-ACFD are the CUT extracted features. The entries of each feature vector can be characterized using linguistic values such as ''very low (VL)'', ''low(LO)'', ''moderate(MO)'', ''high (HI)'', and ''very high (VH)''. Linguistic values are interpreted as values for fuzzy restrictions on some partitioned values of the corresponding feature. These values are represented by fuzzy sets, e.g. A_j^s , where j represents feature index and s represents the corresponding fuzzy set value e.g. s="LO". A fuzzy set A_j^s is characterized by a Membership Function (MF), $\mu_{A_j^s}$, where the MF are degrees to which numerical intensities are compatible with a fuzzy value. For example a Gaussian MF is given by:

$$\mu_{A_j^s} = exp\left(-\frac{(x_j - w_j^s)}{2(\sigma_j^s)^2}\right) \quad (2)$$

where x_j is a value of feature j, w_j^s and σ_j^s are the center and the width of the function, respectively

In order to completely define the fuzzy sets that represent feature j, the parameters of the MF should be defined. Fuzzy C Mean (FCM) clustering algorithm [Jang et al. (1997)] is used to estimate the MF parameters by applying the algorithm to feature j, a vector X_j with an appropriate number of clusters S_j , where $X_j = [x_{ij}]$, and $i = 1,2, \ldots, N_t.(K+1)$ is constructed. Using FCM algorithm, each entry in Xj may belong to more than one cluster with different membership degrees (between 0 and 1). There are two outputs from the FCM algorithm which are:

- centers of clusters c_s, where $s = 1,2, \ldots S_j$.
- membership grades of each value in the X_j to each one of the S_j clusters, these membership grades are arranged in a matrix G^j, where $G^j = [g_{is}^j]$ $i = 1,2, \ldots, N_t.(K+1)$ $and\ s = 1,2, \ldots, S_j$. In this context, g_{is}^j is a membership grade of feature j in pattern number i corresponding to cluster s. The width of the MF, σ_j^s, is calculated as the standard deviation of the input data x_{ij} that has membership grade to cluster s greater than a pre-specified threshold.

Hence, FCM outputs to each cluster are utilized to represent the corresponding MF in the universe of discourse of feature j.

2) *Defining the Outputs*

The outputs of the system are the estimated membership degrees for the input pattern to each fault class. Therefore, there will be as many outputs as fault classes. Each output ye, where $e = 1,2, \ldots K+1$, is quantized into two fuzzy sets B_e^s, where $s = 1,2$, representing two fuzzy values, "low" and "high",

$$B_e^s = \begin{cases} LO\ if\ s = 1 \\ HI\ if\ s = 2 \end{cases} \tag{3}$$

Uniformly distributed Gaussian MF is associated with each fuzzy set. The width of the MFs is 1 and their centers are 0 and 1, respectively.

3) *Defining the Rule Base*

The RB of Mamdani FIS is generally constructed to reflect subjective reasoning using conditional statements (IF-THEN statements). In the proposed FIS-ACFD, the RB is constructed by searching for the appropriate set of rules that describe each fault class. This is achieved by considering the obtained membership grade matrix, H_i , from the FCM clustering algorithm with L_i clusters to the sub-matrix X_i (in X) which has the patterns that represent fault class i. As such, $H_i = [h_{kr}^i] i = 1,2, \ldots, (K+1), k = (i-1).N_{t+1}, \ldots, i.N_t$ and $r = 1,2, \ldots, L_i$. In this context, h_{kr}^i is a membership grade of pattern k that represents fault class i corresponding to cluster r. The repeated rules are then deleted to produce a refinement RB.

4) *Fuzzy Reasoning*

The product operator is selected to combine antecedents and calculate the rule r firing strength $\mu^{(r)}$;

$$\mu^{(r)} = \prod_{j=1}^{R} \mu_{A_j^{(r)}}(x_j) \tag{4}$$

The main reason for using such an operator is to penalize measures falling outside the MF scope. If one of the features falls outside of at least one of the sets defined by the rule antecedents, the final product will be 0, and the rule won't be fired. To calculate the qualified rule consequents, the MF of the THEN-part of rule r is cut at the level indicated by $\mu^{(r)}$. Finally, the overall consequent MF $\mu_{overall}(y_e)$ of the RB is calculated as summation of the qualified consequent MF of the rules.

5) *Defuzzification Method*

The centroid defuzzification method is used as it directly computes the real-valued output as a convex combination of the given fuzzy values for this output contributed from all rules. The fuzzy centroid is unique and uses all information of the output fuzzy set. In particular, the fuzzy centroid $\overline{y}_e$ of the output fuzzy variable y_e , is given by

$$\overline{y}_e = \frac{\int_0^1 y_e \mu_{overall}(y_e) dy_e}{\int_0^1 y_e dy_e} \tag{5}$$

Each output $\overline{y}_e$ is a defuzzified value in the interval [0 1] which represents the membership grade to the corresponding fault class e.

Testing Subsystem

Each output in this system represents an estimated value of the membership degree of the corresponding input pattern to the associated fault class. The classification results need to be compared with the correct class indices in matrices Y and Y_s respectively. Hence, a fuzzy-to-crisp transformation is needed to

map the defuzzified output vector of the FIS-ACFD to a binary vector . Winner-takes all rule is applied which maps the highest component of the outputs to 1 and its other components to 0, respectively;

$$y_e^* = \begin{cases} 1 \; if \; \overline{y}_e = \max_{1 \le d \le K+1}(\overline{y}_d) \\ 0 \qquad otherwise \end{cases} \tag{6}$$

Neuro-Fuzzy Hybridization

The Neuro-fuzzy systems term is usually used for every kind of combination of neural networks and fuzzy systems. Neuro-fuzzy integration is done broadly in two ways: a neural network equipped with the capability of handling fuzzy information, known as fuzzy-neural network (FNN), and a fuzzy system augmented by NNs to enhance some of its characteristics like flexibility, speed, and adaptability, known as neural-fuzzy system (NFS) [Abraham (2001), Pal & Mitra (1999), Wang & Mendel (1992)].

A FNN is a neural network that uses fuzzy methods to learn faster or perform better. In FNN either the input signals and/or the outputs are fuzzy sets. In this case the improvement of the neural network to get better performance is the main intention. An interpretation in terms of fuzzy rules has the second priority here, because the system is based on a neural network with black box characteristics.

The NFS, on the other hand, is designed to perform the process of fuzzy system, where the connection weights of the network correspond to the parameters of fuzzy system. Using the backpropagation-type learning algorithms, the NFS can identify fuzzy rules and learn MF of the fuzzy system. This means that the main intention of the NFS is to create or improve a fuzzy system automatically by means of neural network methods [Aminian et al. (2002)].There are different integrated neuro-fuzzy models (FNS or NFS) that make use of the complementarities of neural networks and fuzzy inference systems. Three well-known neuro-fuzzy models are investigated in this paper: the Adaptive Neural Fuzzy Inference System (ANFIS) [Jang (1993)], the NEuro-Fuzzy approach for the classification of data (NEFCLASS) [Nauck & Kruse (1995)] and Fuzzy Neural Network (FuNN) [Kasabov (1996)]. The first two models are categorized as NFS while the third one as an FNN. In the next section, the implementation of neuro-fuzzy systems in analog fault diagnosis is described.

Implementation of Neuro-Fuzzy Systems for analog circuits fault diagnosis

ANFIS

ANFIS is perhaps the first hybrid NFS. ANFIS is implementing a single output Sugeno FIS [Jang (1993)], the RB is constructed for the purpose of fault diagnosis. An example of the rules that describe fault class i has the following structure

Rule r: IF feature 1 is $A_1^{(r)}$and feature 2 is $A_2^{(r)}$.... and feature R is $A_R^{(r)}$, THEN fault class i for rule r $y_r = a_0 + a_1.feature\ 1 + a_2.feature\ 2 + \cdots + a_R.feature\ R$

In this research, the antecedent part of the RB for the ANFIS is initialized by the same algorithms that is used for building the FIS-ACFD.

ANFIS uses back-propagation learning to determine antecedent parameters and least mean square estimation to determine consequent parameters.

A real-to-integer transformation is used that maps the real value output of the ANFIS classifier into an integer one representing the fault class index. This can be done simply with rounding function.

NEFCLASS

NEFCLASS is an NFS that implements a FIS without MF in the consequent part of the rules. The main components of this FIS for the CUT are the fuzzifier and the RB only. This is due to the structure of the NEFCLASS RB. This FIS uses a rule structure in which the consequent part is attached to the corresponding fault class directly rather than a fuzzy set as in FIS-ACFD or weighted linear combination of the features as in ANFIS. Each fault class can be described by more than one rule with different antecedents. A typical rule that describes fault class i has the following structure;

Rule r: IF feature 1 is $A_1^{(r)}$and feature 2 is $A_2^{(r)}$.... and feature R is $A_R^{(r)}$, THEN the input pattern belongs to fault class i, i.e.,

$$y = (y_1, y_2, \ldots, y_{K+1}) = (\underbrace{0, \ldots, 0}_{i-1}, 1, \underbrace{0, \ldots, 0}_{K+1-i})$$

NEFCLASS uses simple learning strategy to find the rules, and then fuzzy sets are refined by back-propagation-like algorithm. In addition, a pruning algorithm can be applied to reduce the RB [Nauck & Kruse (1995)].

FuNN

FuNN is an example NN and fuzzy system hybridization. It is a connectionist feedforward architecture with five layers of neurons and four layers of connections. Each layer of neurons has a set of parameters that define, respectively, its summation function to aggregate the incoming signals, its activation function to calculate the activation value of the neurons, and its output function to calculate the output values. This multilayer perceptron network is managed to provide a Mamdani FIS with its main components. The structure and the training of FuNNs make it possible to interpret the incoming connection weights to the rule node as degrees of importance (DIs), and the outgoing connection weights from the rule nodes as confidence factors (CFs). Hence, the rule has the following structure [Kasabov (1996)]

Rule r: IF feature 1 is $A_1^1(DI1_{1.r}), A_1^2(DI1_{2.r})$,..., and $A_1^{s^1}(DI1_{s^1.r})$, feature 2 is $A_2^1(DI2_{1.r}), A_2^2(DI2_{2.r})$, ..., and $A_2^{s^2}(DI2_{s^2.r})$,... and feature F is $A_F^1(DIF_{1.r})$, $A_F^2(DIF_{2.r})$, ..., and $A_F^{s^F}(DIF_{s^F.r})$

THEN

y_1 is LO $(CFr_{1,1})$ and HI $(CFr_{2,1})$, y_2 is LO $(CFr_{1,2})$ and HI $(CFr_{2,2})$, ..., and y_{K+1} is LO $(CFr_{1,K+1})$ and HI $(CFr_{2,K+1})$

where $DIj_{s.r}$ is a degree of importance attached to the fuzzy set number s of feature j (i.e A_j^s) corresponding to rule number r, where all fuzzy sets A_j^s have triangular MF with centers $w_j^s, s = 1,2,\ldots,S_j$. On the other hand, $CFr_{s,e}$ is confidence factor attached to the consequent part of the rule number r to the fuzzy set number s for the fuzzy output number , y_e, $s = 1,2$. LO and HI fuzzy sets in the consequent of the rule are defined as two equally distributive triangular fuzzy sets over the interval [0, 1].

Learning in FuNN is based on a modified backprobagation technique that minimizes the output error. A winner-takes all rule is applied to the output defuzzified vector [Kasabov (1996)].

Experimental Results

A benchmark circuit example is presented to demonstrate the potential of the developed procedure, namely, the Sallen-Key band pass active filter circuit.

Sallen-Key Band Pass Active Filter Circuit

The Sallen and Key band pass active filter circuit with nominal value of circuit components is shown in Figure 1. It is considered as a benchmark circuit in analog fault diagnosis [Aminian et al. (2000), Aminian et al. (2002), Abu El-Yazeed & Mohsen (2002)].

The fault free case and 10 soft fault scenarios are considered (K=10). Two soft faults are simulated for 5 components C1, C2, R2, R3, and R4. Component values are toleranced by 50% and -50%, respectively. The simulated fault classes are tabulated in Table 1.

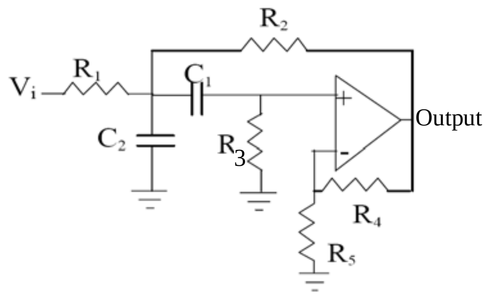

FIG. 1 SALLEN AND KEY BAND-PASS ACTIVE FILTER CIRCUIT
R1= 1 k Ω, R2 = 3 kΩ, R3 =2 kΩ, R4= R5=4 kΩ , and C1 = C2 = 15 nf

TABLE 1 A LIST OF SOFT FAULTS OF SALLEN AND KEY BAND-PASS ACTIVE FILTER WHERE ⇑ REPRESENTS 50% UP THE NOMINAL VALUE AND ⇓ FOR 50% DOWN

Element	Nominal value	Fault class	Fault index	Fault class	Fault index
C1	15nf	⇓	1	⇑	2
C2	15nf	⇓	3	⇑	4
R2	3kΩ	⇓	5	⇑	6
R3	2kΩ	⇓	7	⇑	8
R4	4kΩ	⇓	9	⇑	10

A variable sinusoidal input is applied to the CUT, four frequencies (10 kHz, 16.1 kHz, 26 kHz and 70 kHz) were chosen based on a sensitivity analysis algorithm [Abu El-Yazeed & Mohsen (2002)]

The circuit output is selected as the only test node. For each fault scenario, 200 Monte-Carlo simulations are performed while the output voltage is sampled in the first 0.5 ms with $Ts = 5\,\mu sec$ to get $M = 100$ samples for each waveform. As such the simulated time samples are represented by a (2200x100) matrix.

The WT is utilized as a preprocessor with Haar wavelet family. After applying the WT, the signal is decomposed into approximated and detailed parts. Only the wavelet coefficients of the approximated part $M/2 = 50$ are considered. The PCA is then applied with 5 PCA components ($R = 5$). Then features are normalized to be in the interval [0 1]. Finally, the

reduced feature matrix of dimensions 2200x5 is divided to training matrix X of dimensions 1100x5 (Figure 2) and testing matrix Xs of dimensions 1100x5. The distribution of the input features is shown in Figure 3.

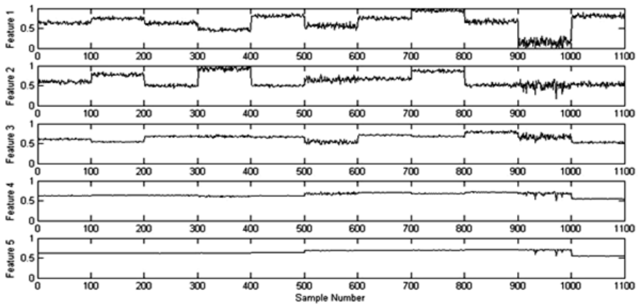

FIG. 2 SELECTED AND EXTRACTED TRAINING FEATURES USING WAVELET TRANSFORM, PCA AND NORMALIZATION FOR EXAMPLE 1

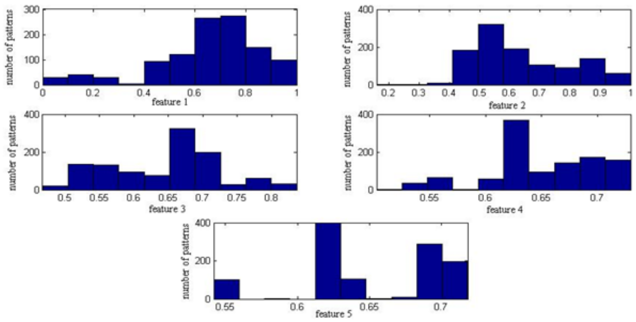

FIG. 3 DISTRIBUTION OF INPUT FEATURES FOR EXAMPLE 1

FIS-ACFD

The structure of the FIS-ACFD, as described in section 3, consists of: a fuzzifier that has certain number of MF for each of the five features, a rule base, and a defuzzifier with 2 MF for each of the 11 outputs (Figure 4). Number of MF that corresponds to a feature is chosen based on the distribution of each feature. The appropriate number of MF is found to be 3 (LO, MO and HI) for each input feature. The RB is constructed by the algorithm described in section 3 with 11 rules, one for each fault class as shown in Figure 5.

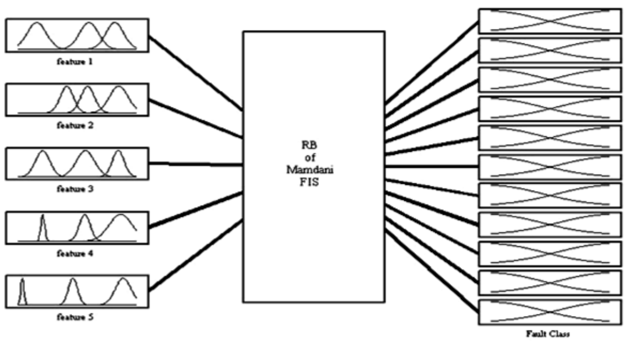

FIG. 4 THE STRUCTURE OF THE FIS-ACFD FOR EXAMPLE 1

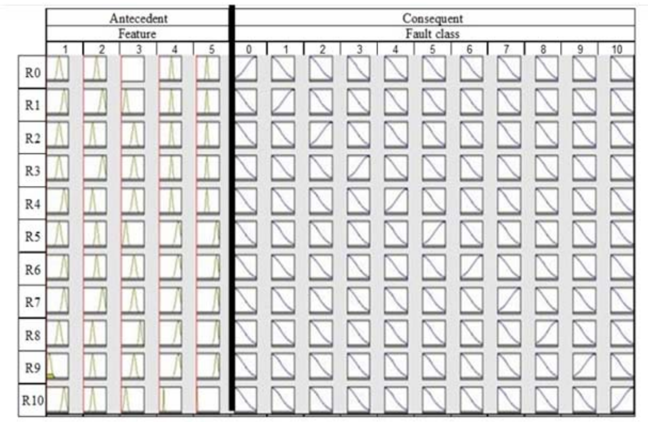

FIG. 5 THE RB OF FIS-ACFD FOR EXAMPLE 1

As an example, the rule that describes fault class 1, R1 in figure 5, can be interpreted as follows;

R1: IF feature 1 is HI and feature 2 is HI and feature 3 is LO and feature 4 is MO and feature 5 is MO THEN fault class 1 is HI and all other fault classes are LO

As a result of using ANFIS, the diagnosis performance is 99.18% for both recall capability and adaptability.

ANFIS

The structure of the RB antecedents is initialized to be the same as the RB of the FIS-ACFD. Due to random initialization of consequent parts, the recall capability percentage and the adaptability percentage are measured for 20 ANFISs that are initialized with different random consequents. The average diagnosis performance was 99.73% for both recall capability and adaptability.

NEFCLASS

The RB is constructed by determining the best rules per class. A total of 14 rules are constructed. The diagnosis performance of the trained NEFCLASS is 99.73% and 99.18% for recall capability and adaptability, respectively.

The RB and fuzzy representation of features are interpretable as in the FIS-ACFD. Although better diagnosis performance is achieved, more rules are needed compared to ANFIS, NEFCLASS is simpler in training and has more interpretable RB.

FuNN

The network structure of FuNN has 5 nodes for the first layer which is the number of input features, 15 nodes for the second layer that represent 3 MF for each feature, 22 nodes for the forth layer which are

corresponding to 2 MF for each output and 11 output nodes for the fifth layer. The MF of the inputs and outputs (i.e. the input and output connection weights) do not change during the training time because a modified BP algorithm is used for the purpose of rule adaptation. The FuNN model with 7 rules (i.e., 7 nodes in the third layer) has achieved the best performance. The FuNN has 100% diagnosis performance, both for recall capability and adaptability.

The results obtained here are compared with the results obtained for the same CUT using NN-based classifiers [Aminian et al. (2002), Abu El-Yazeed & Mohsen (2002)]. Aminian et al. [Aminian et al. (2002)] used a feed forward NN as a classifier. The impulse response of the CUT, at test node 1, was simulated at fault-free case, in addition to 8 soft fault scenarios. Two soft faults are simulated for each of the circuit components R2, R3, Cl, and C2. Component values are tolerated by + 50% and – 50% in the fault scenarios. For each fault, a training set of 20 patterns, each having 4 wavelet features, is used to train the NN classifier. The system achieves a classification accuracy of 97% when tested by 40 patterns for each fault scenario [Aminian et al. (2002)]. Abu El-Yazeed et al.[Abu El-Yazeed & Mohsen (2002)] considered the same circuit in a fault diagnosis system using Auto Regressive Moving Average (ARMA) model as a preprocessor and a BP neural network as a classifier. The used classifier was not able to distinguish between the fault-free and the (R2⇑) faulty condition. 6 more fault scenarios are simulated for the circuit components R1, R4, and R5. The system achieved a classification accuracy of 99.58% in testing when the number of nodes in the hidden layer is set to 12. The above results demonstrate the superior performance of the fuzzy and neuro-fuzzy approaches compared to other NN-based approaches.

Conclusions

This paper demonstrates the capability of the FIS and neuro-fuzzy models to isolate faults in analog circuits. A novel fuzzy inference system is efficiently designed to characterize different faults of the CUT. A rule base for each fault that relates measurements to faulty elements is constructed. Training data was preprocessed using WT and PCA. Three prominent neuro-fuzzy models are also exploited in modeling circuit faults. The superior diagnosis performance of the proposed approach is attributed to the fusion of NNs and FIS during the training phase in which numerical data as well as linguistic knowledge are combined. Testing the classifiers on a benchmark circuit showed the following conclusions:

- The proposed FIS for analog fault diagnosis has relatively good and interpretable diagnosis performance despite the absence of learning ability.
- In general, neuro-fuzzy systems have better diagnosis performance than the fuzzy systems.
- Regarding the diagnosis performance, FNN represented by FuNN proved to outperform the NFS represented by ANFIS and NEFCLASS.
- The proposed algorithm for defining input MF and RB is utilized efficiently in initialization of ANFIS.
- ANFIS needs a prior estimation of the system structure i.e. rules and MF, however; it has a powerful learning technique that changes RB parameters.
- Although NEFCLASS has flexible number of rules which are determined by simple learning technique, it needs a prior estimation for the number of MF. Moreover, it is inefficient for large diagnosis problems due to the training technique simplicity. On the other hand, it is the most interpretable classifier.
- Although FuNN has a superior diagnosis performance due to NN nature, it needs a prior estimation of the number of rules and number of MF. Also, like any NN based classifier, FuNN has the drawbacks of needing a long time in the training phase and large computational effort in the testing phase, especially for large number of rules.
- FuNN has a better performance than the NN-based techniques that are applied in the literature for the same CUT.

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M. A. El-Gamal received his BSC degrees in Electronics Engineering from Cairo University and in Applied Mathematics from Ain Shams University in 1977 and 1980 respectively. He received his M SC and Ph. D. degrees from Ohio University, Athens, Ohio in Electrical and Computer Engineering in 1985 and 1990 respectively.

He worked as a teaching and research assistant at Ohio

University from 1985 to 1990. In 1987, he joined the National Institute of Standards and Technology, Gaithersburg, Maryland as a guest scientist for six months. Since 1991, Dr. El-Gamal is with the Department of Engineering Mathematics and Physics, Faculty of Engineering, Cairo University where he is now a Professor. From 1993 to1999 he was on leave with the Department of Computer Science at the United Arab Emirates University.

Dr. El-Gamal is an author and a co-author of more than 35 research papers published in international research journals and conferences. He also supervised a large number of master and doctorate students. His research interests include fault diagnosis of analog and mixed signal circuits, neural network- based classification algorithms and applications of fuzzy logic and genetic algorithms.

Samah El-Tantawy is a postdoctoral fellow at the ITS Lab and Testbed, University of Toronto. Samah completed her PhD in 2012 in the field of ITS at University of Toronto. She completed her Bachelor degree in Electrical and Communication Engineering, Cairo University in 2004 and her M.Sc. degree in Engineering Mathematics, Cairo University in 2007. Right after finishing her M.Sc., she was awarded the PhD Connaught Scholarship from University of Toronto. For her PhD research, Samah developed a coordinated traffic signal control system using game theory concepts and multi-agent reinforcement learning approaches (MARLIN-ATSC). She has few published journal papers and ten conference papers. She also has filed a US provincial patent. She won four industrial scholarships (ITS Canada, TAC, CTRF, and CITE) and three provincial scholarships (two Ontario Graduate Scholarships (OGS) and OGS in Science and Technology (OGSST)). Samah's developed technology, MARLIN-ATSC, has won the MaRS Innovation Proof of Principle (PoP) funding for 2012 to conduct system integration for MARLIN into a real controller and field implementation system requirements. Samah won two international awards for her dissertation in 2013; namely, the IEEE-ITSS Best PhD Dissertation Awards, First Place, and INFORMS George B. Dantzig Dissertation Awards, Finalist. Samah was the vice president of the Institute of Transportation Engineers (ITE) student chapter at UofT for 2010 and 2011, an IEEE member, a member in the Women in ITS group (WITS) and IEEE Women in Engineering (WIE), and a friend of the Traffic Signal Systems TRB Committee.